Semantic Segmentation of Breast Ultrasound Image with Pyramid Fuzzy Uncertainty Reduction and Direction Connectedness Feature

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Abstract

A novel deep neural network structure is developed combining with fuzzy logic and a novel context feature. The architecture is applied to breast ultrasound (BUS) image semantic segmentation. It has the following contributions:

- The proposed approach can measure the uncertainty degree for pixels in different resolution levels.
- Entropy of memberships is utilized to calculate uncertainty degree for pixels.
- The novel context feature can reflect the layer structure of breast.

Introduction

Breast cancer occurred frequently in women over the world. Breast ultrasound (BUS) imaging is the most important approach for breast cancer early detection.

To overcome the noise and uncertainty in BUS image, fuzzy logic is integrated into deep neural network. Meanwhile, a novel context feature is calculated based on the connectedness between each pixel and boundary pixels along four horizontal and vertical directions (left, right, up, and down). It can reflect the breast layer structure.

Methods and Dataset

The proposed network structure is shown in Fig. 1 (b). The U-shape network with VGG-16 (Fig. 1 (a)) is chosen as the base network. The proposed pyramid fuzzy block and the direction connectedness feature are added to the base network.

The proposed pyramid fuzzy block consists of four parts:

1. Down-sampling

The input feature map $X^0 \in \mathbb{R}^{M\times N\times D}$ is down-sampled twice to $X^1 \in \mathbb{R}^{\frac{M}{2}\times\frac{N}{2}\times D}$ and $X^2 \in \mathbb{R}^{\frac{M}{4}\times\frac{N}{4}\times D}$. M, N, and D represent the width, length, number of channels of input feature map.

Methods and Dataset

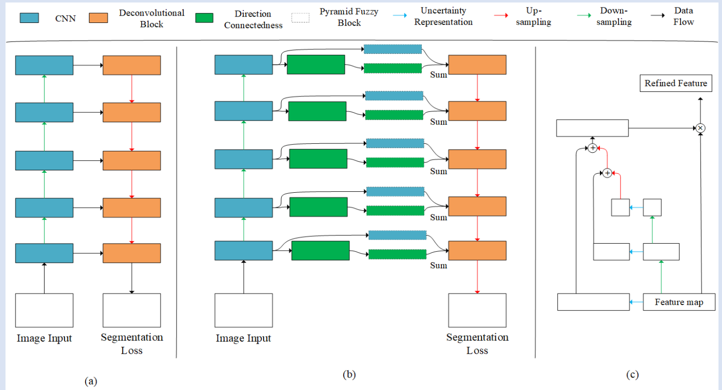

Figure 1. Structure of the proposed network.

2. Fuzzification

$$\mu_{ik}^{l} = \frac{1}{1 + e^{\alpha_{ik}^{l} x_i^{l} + \beta_{ik}^{l}}}$$

where $x_i^l \in \mathbb{R}^D$ is the ith pixel in feature map X^l, l = 0, 1, 2. $\alpha_{ik}^l \in \mathbb{R}^D$ and $\beta_{ik}^l \in \mathbb{R}^D$ are two trainable parameters for membership function in the kth category. $\mu_{ik}^l \in \mathbb{R}$ represents the membership in the kth category.

3. Uncertainty representation

$$u_i^l = -\frac{1}{\ln C} \times \sum_{k=1}^{C} \mu_{ik}^l \ln \mu_{ik}^l$$

C represents the number of categories.

4. Uncertainty reduction

$$u = \mathrm{Up\_sampling}((\mathrm{Up\_sampling}(u^2) \oplus u^1) \oplus u^0)$$
$$X' = X^0 \otimes (1 - u)$$

$u^l = (u^0, u^1, u^2)$ is obtained by u_i^l.

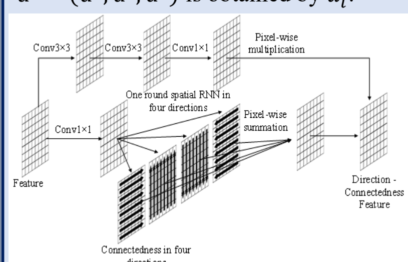

Figure. 2 Direction connectedness feature extraction block.

The flowchart of the proposed direction connectedness feature extraction block is shown in Fig. 2.

Dataset:

1. A multi-object BUS image dataset with 325 images and 5-category pixel-wise ground truths: fat layer, mammary layer, muscle layer, background, and tumor.

2. A public dataset available at: http://cvprip.cs.usu.edu/busbench/.

Results

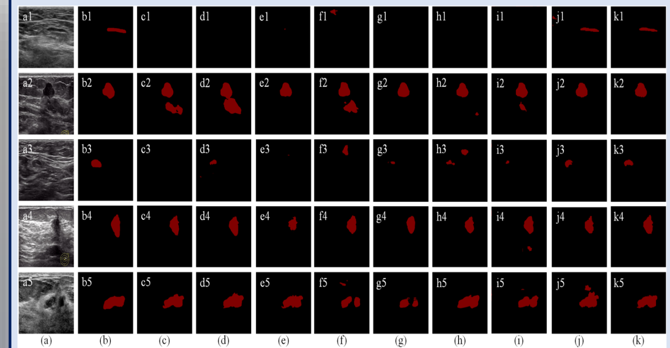

Figure 3. Segmentation results using the public dataset: (a) original images; (b) ground truths; (c) results of U-Net; (d) results of ResNet-50; (e) results of ResNet-101; (f) results of Deeplab; (g) results of PSPNet; (h) results of U-Net with wavelet transform; (i) results of FCN-8s; (j) results of U-Net with DSC feature; (k) results of the proposed method.

Table I Evaluation results on public BUS image dataset

	TPR	FPR	IoU	DS	AER
U-Net	0.92	0.09	0.86	0.92	0.17
Deeplab	0.89	0.11	0.82	0.89	0.22
ResNet50	0.92	0.08	0.86	0.92	0.16
ResNet101	0.92	0.10	0.85	0.91	0.18
FCN-8s	**0.94**	0.10	0.86	0.92	0.16
PSPNet	0.93	0.09	0.86	0.92	0.16
U-Net + wavelet	0.92	0.09	0.86	0.92	0.16
DSC	0.91	0.10	0.84	0.91	0.18
Proposed	0.93	**0.07**	**0.87**	**0.93**	**0.15**

Conclusions

The proposed method achieves the best overall performance in binary semantic segmentation and multi-object semantic segmentation for BUS image compared with eight deep learning-based approaches. Here, we just show the results in using the public dataset. The proposed method achieves good results by 1) reducing uncertainty of feature maps using fuzzy logic in different resolutions; 2) applying a novel context feature which can reflect breast horizontal layer structure.